

Evaluation of CHIRPS Satellite Gridded Dataset as an Alternative Rainfall Estimate for Localized Modelling over Uganda

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Abstract

The Ugandan economy is largely dependent on rural-based and rain-fed agriculture. This creates a critical need to understand the rainfall dynamics at the local scale. However, the country has a sternly sparse and unreliable rain gauge network. This research, therefore, sets out to evaluate the use of the CHIRPS satellite gridded dataset as an alternative rainfall estimate for local modelling of rainfall in Uganda. Complete, continuous and reliable *in situ* station observations for the period between 2012 and 2020 were used for the comparison with CHIRPS satellite data models in the same epoch. Rainfall values within the minimum 5 km and maximum 20 km radii from the *in situ* stations were extracted at a 5 km interval from the interpolated *in situ* station surface and the CHIRPS satellite data model for comparison. Results of the 5 km radius were adopted for the evaluation as it's closer to the optimal rain gauge coverage of 25 km². They show the $R^2 = 0.91$, $NSE = 0.88$, $PBias = -0.24$ and $RSR = 0.35$. This attests that the CHIRPS satellite gridded datasets provide a good approximation and simulation of *in situ* station data with high collinearity and minimum deviation. This tallies with related studies in other regions that have found CHIRPS datasets superior to interpolation surfaces and sparse rain gauge data in the comprehensive estimation of rainfall. With a $0.05^\circ \times 0.05^\circ$ (Latitude, longitude) spatial resolution, CHIRPS satellite gridded rainfall estimates are therefore able to provide a comprehensive rainfall estimation at a local scale. Essentially these results reward research science in regions like Uganda that have sparse rain gauges networks characterized by incomplete, inconsistent and unreliable data with an empirically researched alternative source of rainfall estimation data. It further provides a platform to scientifically interrogate the rainfall dynamics at a local scale in order to infuse local policy with evidence-based formulation and application.

Keywords

Spatial Statistics, CHIRPS, Satellite Gridded Dataset, Rainfall Estimates

1. Introduction

Precipitation is one of Uganda's most critical and valuable resources. Its availability and variability have direct implications on the country's overall development given the predominance of rain-fed agriculture [1]. Indeed, rain-fed agriculture and agriculture-related production are vital to the Ugandan economy; they averagely employ 80% of the labour force, account for 42% of the GDP, and bring in 90% of export earnings [2] [3]. However, Uganda is in the deficit of a dense rain gauge network and long-term *in situ* precipitation measurements are required for detailed assessment of her rainfall [4] [5]. The rain fall records are typical of non-continuity with only a few years of quality data, sparse rain gauge network, incomplete, inconsistent and non-reliable datasets. Notably, understanding the dynamics of climate variations and extremes that are consistent with the region requires long-term accurate precipitation data representations and a dense network of *in situ* observation stations [6] [7]. The World Meteorological Organization (WMO) set the classical period of assessing climate variability to 30 years.

Research [8] puts the optimum rain gauge network density between 14 km²/gauge and 38 km²/gauge, with an average of 25 km²/gauge. With Uganda having a total area of 241,550 km², this puts the total gauge requirement per 25 km² close to about 9500 weather stations. However, as of 2013, Uganda had 21 weather stations [9]. With the proliferation of automated weather stations, as of 2021, the total number of weather stations had been improved to 37. Incidentally, of these, 25 are working, 7 were vandalized and 5 had power problems. This puts the total landmass covered to 625 km² out of the total 241,550 km², accounting for only 0.0026% gauge coverage. This has characterized the country with a critically sparse and unreliable rain gauge network. Traditionally, it should be noted that set rain gauges are affected by animal and human interference, uncalibrated measuring mechanisms, level placement, wind, poor monitoring and evaporation [10] [11] [12]. This further worsens the dependency on completeness and consistency of *in situ* measurements from rain gauges. Also, relative to satellites that can provide precise measurements at every location, for developing countries, the sparsely distributed weather stations are characterized by poor coverage for rural areas and require interpolation between stations [13] to relay general coverage of a region. This makes the reliance on satellite data sets inevitable to achieve alternative estimates of rainfall with adequate sampling density, accuracy, completeness and reliability. However, satellite-based precipitation estimates are often not assessed for integration into operational and decision-making applications due to the lack of empirical research on their uncertainty and reliability [14]. For Uganda,

no explicit countrywide empirical research has been done to assess the suitability of satellite gridded precipitation datasets as an alternative rainfall estimate at a local scale. It should be noted that the region is challenged with scarce and inconsistent precipitation data. The objective of this research was, therefore, to evaluate satellite gridded datasets as an alternative rainfall estimate for modelling rainfall at a local scale. The research will enable satellite-based precipitation estimates to be integrated into the operational analysis of rainfall dynamics as a proxy for *in situ* rainfall data in Uganda.

2. Satellite Gridded Datasets as Alternative Rainfall Estimates

Numerous satellite gridded precipitation data sets exist at a global and regional scale [15]. Though satellites have trouble measuring some ground phenomena such as precipitation as compared to weather stations, they provide a more complete spatial coverage of various parameters over a landscape [13]. This has prompted research to understand the contrast between the two sets of data. Throughout the literature, several studies have compared satellite remote sensing products to *in situ* data [16] [17] [18] [19] [20]. The satellite-based datasets have generally presented a better performance at annual and seasonal scales. Some scholars [21], explored the performance of stochastic models for spatial rainfall down-scaling to reproduce statistics for precipitation observable at a local scale. The analysis, however, would not allow preference among the studied models. Other scholars [22] have explored algorithms of blending the *in situ* measurements with satellite observations to derive more accurate products for local rainfall analytics. However, none of the research has been conclusive leaving a gap in the analysis of local precipitation using satellite gridded rainfall estimation datasets.

3. Materials and Methods

3.1. Study Area

This research was carried out within the spatial domain of the Republic of Uganda. Uganda is a landlocked country in the eastern part of Africa and lies within the northern and southern hemispheres, being crossed by the Equator. Neighboring countries are Kenya to the East, South Sudan to the North, the United Republic of Tanzania and Rwanda to the South and the Democratic Republic of Congo to the West. According to [23], the country has a total surface area of 241,550 km² of which 41,743 km² (17.2%) is occupied by open water and swamps, and 199,807 km² is open land. Uganda is a plateau surrounded by four main mountain ranges; namely: Rwenzori in the west (with a peak of 5110 m), Elgon in the East, Mufumbira in the Southwest, and Moroto in the Northeast. The lowest part is within the Albert Nile at 620 m above sea level. This topographic complexity is associated with a high density of micro-environments where climatic variables become difficult to study [24]. In essence, this makes the area suitable

spatial resolution while the African Rainfall Climatology version 2 (ARC2) and Tropical Rainfall Measuring Mission (TRMM) have a spatial resolution of $0.1^\circ \times 0.1^\circ$ and $0.25^\circ \times 0.25^\circ$ respectively.

3.2.2. *In Situ* Measurements

In Situ precipitation data was gotten from Uganda National Meteorological Authority (UNMA). The data was for multiple weather stations. However, the datasets were assessed for completeness, continuity, consistency, and reliability. On this basis, only 12 of the 25 data stations were utilized. Their distribution is illustrated in **Figure 2**. Though long time series are often required, the datasets used in this research were for the temporal period of 2012 to 2020. Beyond this period there were no sufficient datasets that fulfilled the criteria suitable for effective comparison with the gridded datasets.

4. Statistical Metrics

Spatial Inference research on precipitation studies has utilized a vast continuum of statistical criteria to assess agreement between models [24] [27] [28]. This research adopted the statistical metrics shown in **Table 1**.

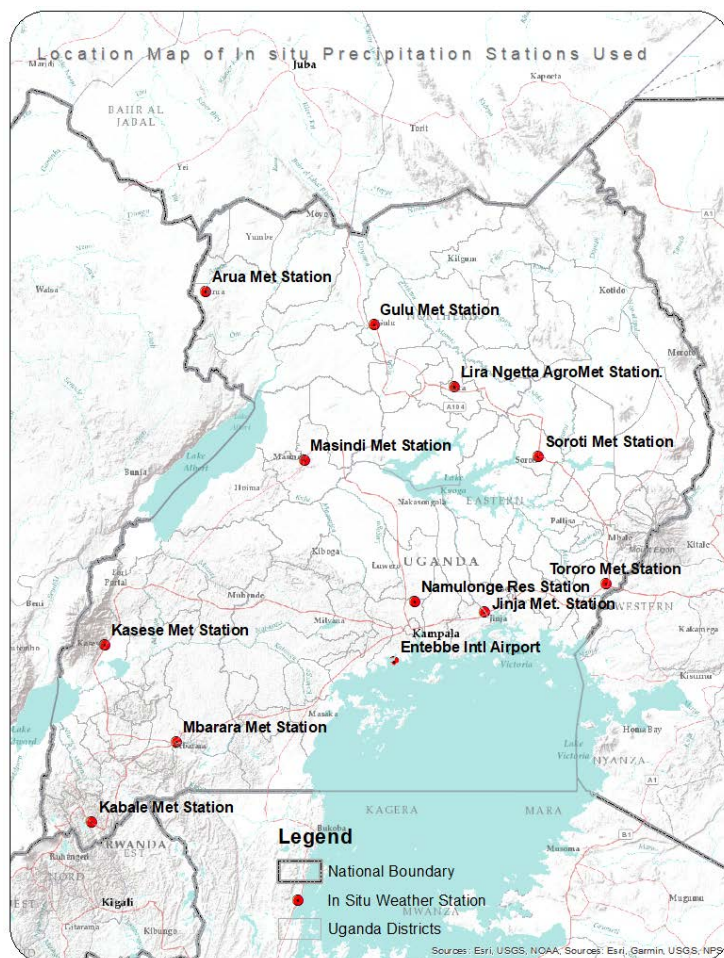


Figure 2. Location map of the *in situ* precipitation stations.

Table 1. Adopted statistical metrics.

Statistic	Formula	Range	Best value	Conditioning
Coefficient of determination	$R^2 = \left[\frac{\sum_{i=1}^N (INS_i - \overline{INS_i})(INS_i - \overline{SAT_i})}{\sum_{i=1}^N (INS_i - \overline{SAT_i})^2 \sum_{i=1}^N (SAT_i - \overline{SAT_i})^2} \right]^2$	0 to 1	1	Describes the proportion of variance in the <i>in situ</i> data that are accounted for by the satellite data the closer to 1 the better [30].
RMSE-Observation standard deviation ratio	$RSR = \left[\frac{\sum_{i=1}^N (INS_i - SAT_i)^2}{\sigma_{INS}^2} \right]$	0 to ∞	0	A low RSR is directly proportional to the Root Mean Square Error (RMSE). The closer it is to zero the better [31].
Nash-Sutcliffe efficiency coefficient	$NSE = 1 - \left[\frac{\sum_{i=1}^N (INS_i - SAT_i)^2}{\sigma_{INS}^2} \right]$	$-\infty$ to 1	1	The normalized statistic determines the relative magnitude of the residual variance of the satellite observation in comparison to the <i>in situ</i> measured variance [31]. The closer the value is to 1 the better.
Bias percentage	$PBias = \frac{\sum_{i=1}^N SAT_i - \sum_{i=1}^N INS_i}{\sum_{i=1}^N INS_i} * 100$	$-\infty$ to ∞	0	Measures the average tendency of satellite models to be smaller or larger than the <i>in situ</i> measurement [32]. Low values close to zero (0) indicate accurate simulation of the satellite data, positive values indicate underestimation while negative values indicate overestimation [31].

5. Methodology (Figure 3)

Datasets collected from the weather stations were assessed for consistency, completeness and continuity for the study period between 2012 and 2020. The data were interpolated between stations across the country. The validity of the resulting interpolation was assessed through independent weather stations (15% of the original weather stations) repetition were used to validate the Interpolation. The geostatistical ordinary Kriging was used as previous studies showed that it achieved the best results in precipitation interpolation [24] [33]. A fishnet was generated over Uganda with a 5 km point grid. Buffers of 5 km to 20 km from the *in situ* measurement stations were generated to clip the points of the fishnet. The clipped points were used for the extraction of values from the interpolated surface and satellite gridded dataset (CHIRPS). A bivariate linear regression was run between the extracted values of the interpolation surface and the CHIRPS surface in iteration to acquire the best sample points extraction range for comparing the two surfaces at an R^2 greater than 0.75. This was in consideration of [8] analysis on optimal distance for *in situ* station coverage. Buffers of 5 km and 20 km were chosen as the furthest and nearest ranges for further analysis of the comparison between the CHIRPS satellite gridded dataset and *in situ* station measurement rainfall estimates (the minimum 5 km range was chosen because the CHIRPS has a $0.05^\circ * 0.05^\circ$ (latitude, longitude) spatial resolution). These were subjected to further spatial statistical metrics shown in **Table 1** to derive a detailed evaluation of the relation between the two surfaces.

6. Results and Discussion

Precipitation data from the *in situ* weather stations was mapped by Kriging

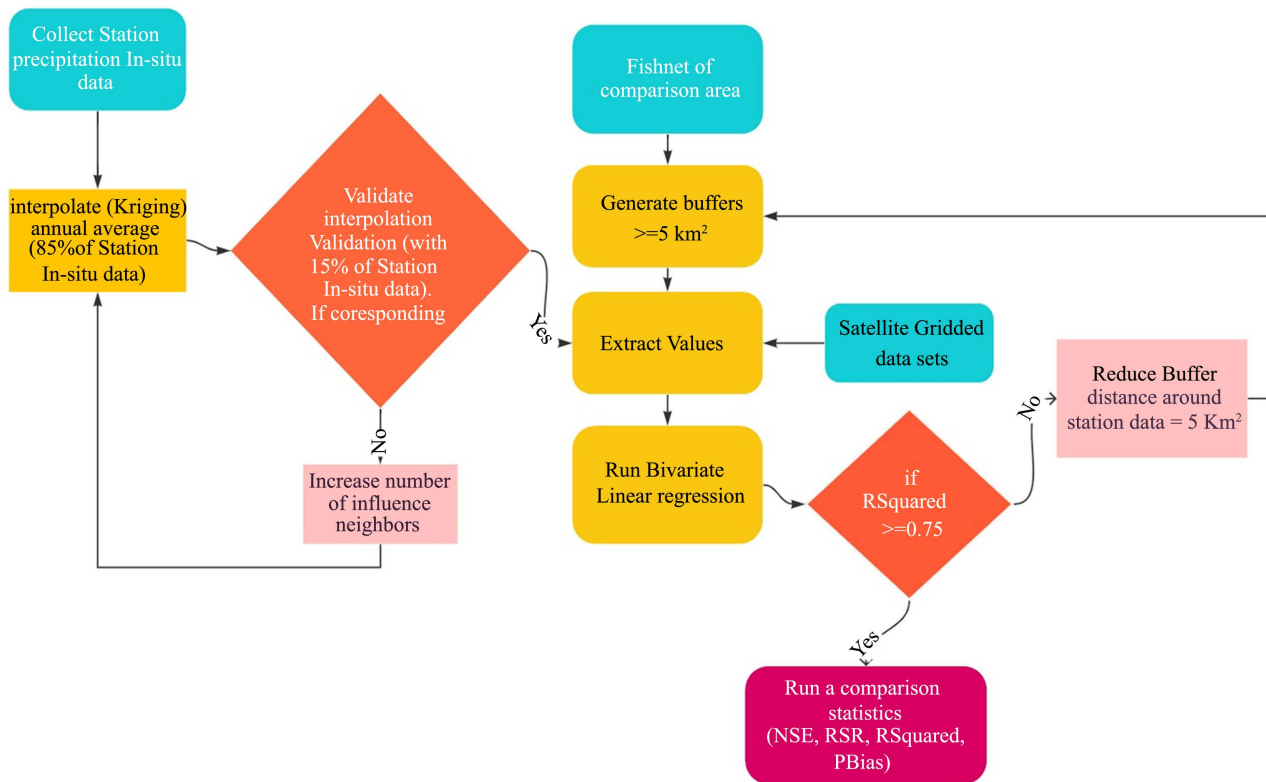


Figure 3. Methodology flow diagram.

interpolation for each year as shown in **Figure 4**. The results showed an average representation of most precipitation being received along the northwest-southeast belt and the Lake Victoria basin. From the results, it can also be deduced that the southwest-northeast belt received less rainfall. This is consistent with observations of the cattle corridor that show a pronounced increase in dry spells along the southwest-northeast corridor [34]. Related research [35] also observed the highest rainfall in the north-west and central east of Uganda and Lake Victoria vicinity

Satellite gridded datasets were collected for the same epoch (2012-2020) as the *in situ* data sets and mapped as shown in **Figure 5**. Similar to observations by [35] the lowest precipitation totals are in the northeast (Karamoja region) and the south-west while the highest levels of precipitation are observed in the Lake Victoria vicinity, central-east and north-west.

Research [8] approximates optimal rain gauge coverage to about 25 km² beyond which the quality of representation drops. From the *in situ* measurement positions in **Figure 2**, buffers points at 5 km intervals were generated as shown in **Figure 6** for extraction of values from each surface at minimum 5 km and maximum 20 km ranges.

Between the *in situ* and satellite observations at 5 km, the coefficient of determination (R^2) showed very strong collinearity of 0.91 as shown in **Figure 7**. The Nash-Sutcliffe Efficiency (NSE) coefficient = 0.88, Percentage of Bias (PBias) = -0.24, and the RMSE-observations Standard deviation Ratio (RSR) = 0.35.

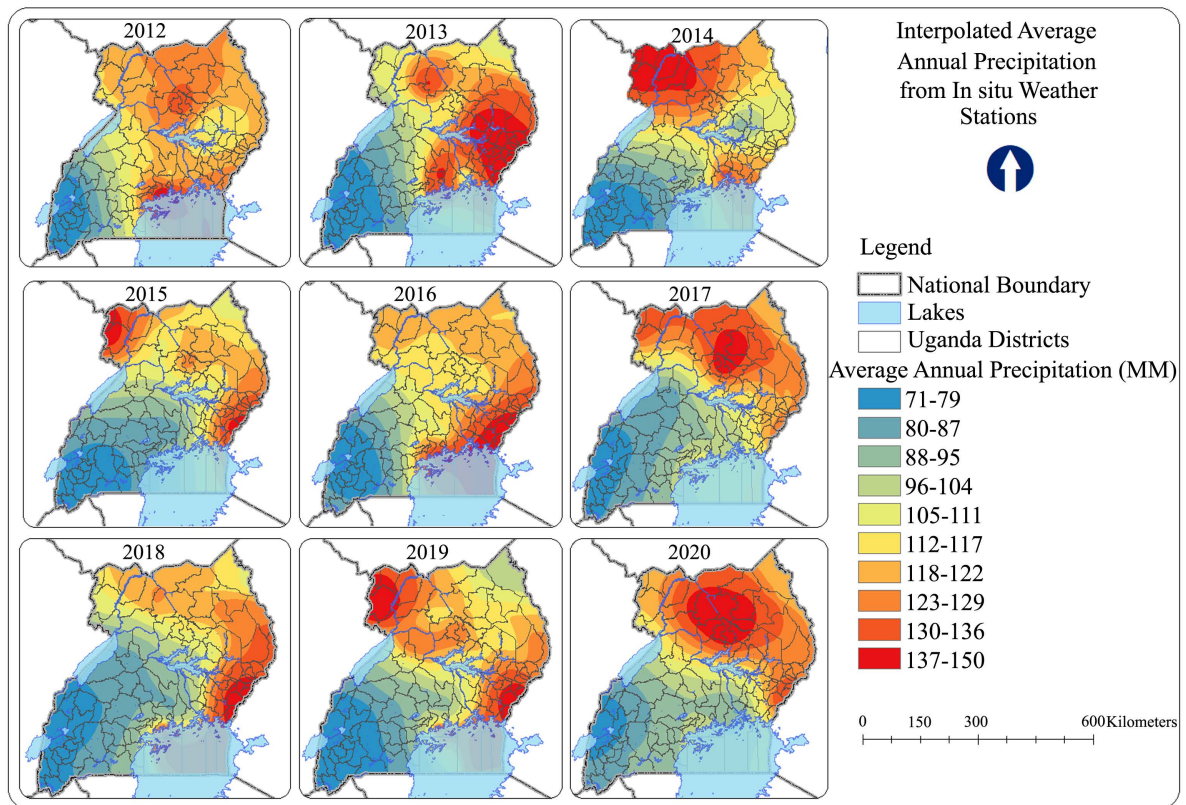


Figure 4. Interpolated average annual precipitation.

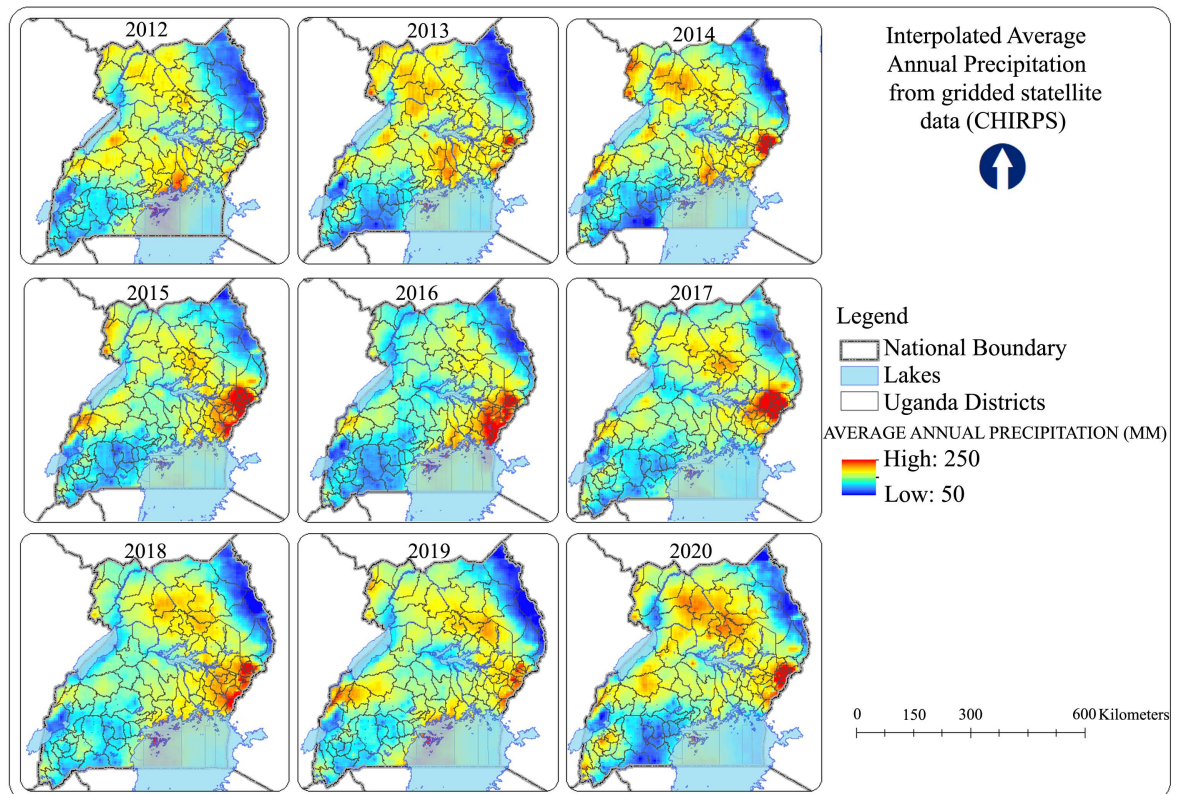


Figure 5. Average annual precipitation from satellite gridded data sets—CHIRPS.

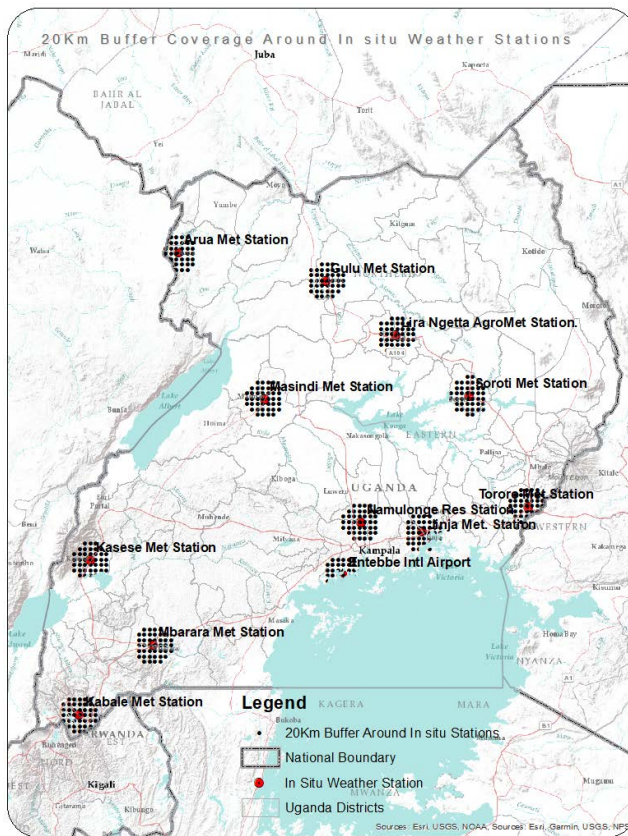
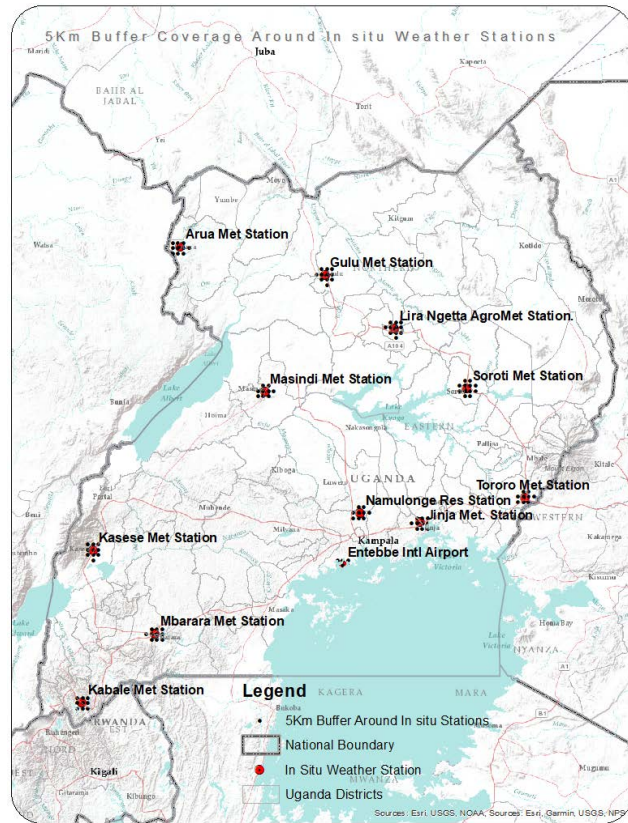


Figure 6. 5 km and 20 km sample range.

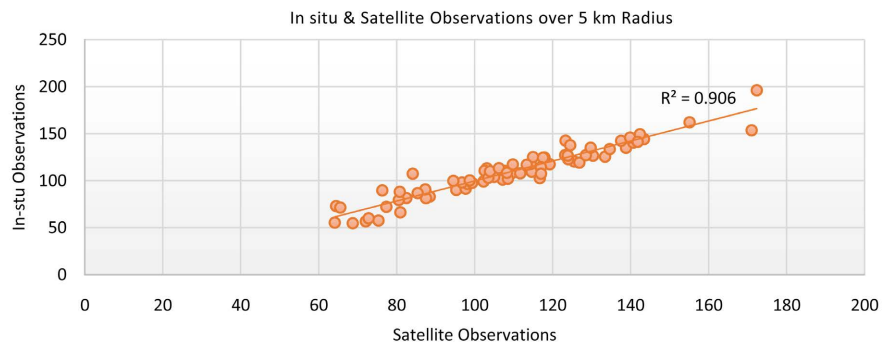


Figure 7. Collinearity between *in situ* and satellite precipitation observations within a 5 km radius of the weather station.

Between the *in situ* and satellite observations at 20 km, the coefficient of determination (R^2) showed strong collinearity of 0.75 as shown in **Figure 8**. The Nash-Sutcliffe Efficiency (NSE) coefficient = 0.461, Bias Percentage (PBias) = 0.84, and the RMSE-observations Standard deviation Ratio (RSR) = 0.51.

Several studies [36] [37] have adopted the performance rating of the statistical metrics R^2 [30], and RSR, NSE, PBias [31] shown in **Table 2**. According to this rating, at 5 km there is very good collinearity between the *in situ* data and the CHIRPS satellite model with an R^2 of 0.91. This implies that a high proportion of the variance in the *in situ* observations is accounted for in the CHIRPS gridded satellite observations. The RSR of 0.35 low value at 5 km indicates a very good approximation by the CHIRPS satellite model. The 0.88 NSE also implies a very good simulation of *in situ* data by the CHIRPS satellite data. The PBias of -0.24 indicates minimal deviation of the data being evaluated which also accounts for the very good simulation by the CHIRPS model. At 20 km an R^2 of 0.75 indicated a good collinearity between the *in situ* and satellite observation. The RSR of 0.51 also indicated a good approximation of the *in situ* data by the CHIRPS satellite model. The PBias of 0.84 also indicated an acceptable deviation between the *in situ* data and the gridded satellite data. However, the NSE of 0.461 indicated an unsatisfactory simulation of the *in situ* data by the CHIRPS satellite model.

Similar statistical metrics were run for each of the *in situ* stations and its 5 km and 20 km radius as shown in **Table 3**. Within the 5 km radius, 75% of the stations presented with an R^2 above 0.86 indicating very good collinearity between the *in situ* observations and CHIRPS satellite data model. However, the Kabale station presented an unsatisfactory R^2 of 0.44. Also, 60% of the stations indicated an above satisfactory RSR statistic indicating a good approximation of the *in situ* data by the CHIRPS satellite data model. Correspondingly, 65% of the stations presented an NSE statistic above satisfactory indicating an acceptable simulation of *in situ* data by CHIRPS satellite gridded data. All the stations had above satisfactory PBias indicating acceptable deviation between the two datasets. At 20 km, only 25% of the records presented R^2 and RSR above satisfactory levels indicating low levels of collinearity and approximation between the models, 40%

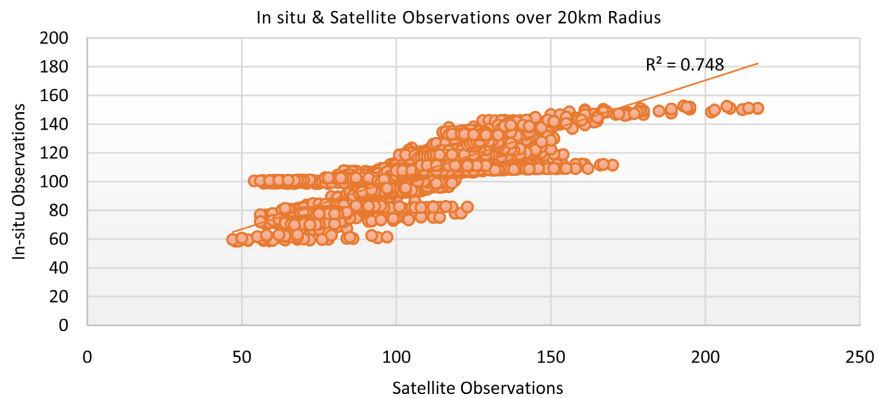


Figure 8. Collinearity between *in situ* and satellite precipitation observations within a 20 km radius of the weather station.

Table 2. Performance rating of the statistical metrics.

Performance Rating	RSR	NSE	PBIAS	R ²
Very Good	$0.00 \leq \text{RSR} \leq 0.50$	$0.75 \leq \text{NSE} \leq 1$	$\text{PBIAS} < \pm 10$	$0.86 < \text{R}^2 \leq 1$
Good	$0.60 < \text{RSR} \leq 0.50$	$0.65 < \text{NSE} \leq 0.75$	$\pm 10 \leq \text{PBIAS} \leq \pm 15$	$0.75 < \text{R}^2 \leq 0.86$
Satisfactory	$0.70 < \text{RSR} \leq 0.60$	$0.50 < \text{NSE} \leq 0.65$	$\pm 15 \leq \text{PBIAS} \leq \pm 25$	$0.65 < \text{R}^2 \leq 0.75$
Unsatisfactory	$\text{RSR} > 0.7$	$\text{NSE} \leq 0.50$	$\text{PBIAS} \leq \pm 25$	$\text{R}^2 \leq 0.65$

Table 3. Statistical metrics at 5 km and 20 km sample range of *in situ* weather stations.

<i>In Situ</i> Station	Statistical Metrics at 5 km Per Station				Statistical Metrics at 20 km Per Station			
	NSE	PBIAS	R ²	RSR	NSE	PBIAS	R ²	RSR
Arua	0.88	0.17	0.88	0.35	0.16	-0.58	0.46	0.92
Entebbe	0.91	-1.75	0.97	0.3	0.5	6.18	0.62	0.71
Gulu	0.24	4.1	0.89	0.87	0.46	3.24	0.64	0.74
Jinja	0.63	-1.56	0.66	0.61	0.69	2.48	0.76	0.55
Kabale	-0.04	-8.64	0.41	1.02	-0.01	-6.13	0.5	1
Kasese	0.82	2.79	0.87	0.43	-0.51	-7.18	0.02	1.23
Lira	0.34	-8.91	0.9	0.81	0.45	3.21	0.67	0.74
Masindi	0.71	-4.48	0.95	0.54	0.66	-3.45	0.77	0.59
Mbarara	0.89	0.31	0.92	0.33	0.05	-6.33	0.53	0.97
Namulonge	-6.24	19.08	0.74	2.69	0.58	2.78	0.63	0.65
Soroti	0.47	5.36	0.94	0.73	0.22	-1.95	0.57	0.88
Tororo	0.96	-0.89	0.97	0.21	0.08	10.26	0.47	0.96

of the stations presented an NSE statistic above satisfactory level implying that more than 60% of the *in situ* observation couldn't be interpreted at this range. However, the PBIAS indicated acceptable deviations between the two models.

7. Conclusion

The assessments and monitoring of precipitation variation, changes and extremes are critical to an agriculturally based economy. However, for Uganda, the availability of consistent, complete, and reliable precipitation data required for this monitoring and assessment has remained a challenge. This research sets out to validate the use of CHIRPS satellite gridded data sets as an alternative source of precipitation data. Based on the [8] review of best rainfall *in situ* observations being in the optimal range of 25 km², this research forms an evaluation basis to validate the use of CHIRPS satellite gridded dataset as an alternative precipitation estimation dataset by comparing the 5 km range and radius sample points between surfaces of interpolated *in situ* surfaces and CHIRPS satellite dataset. It further shows that widening the validation area beyond the optimal coverage of the rain gauge generates dwindling effects on the validation between the *in situ* and CHIRPS satellite gridded dataset surfaces. Spatially based statistical metrics that include the coefficient of determination (R^2), the Nash-Sutcliffe Efficiency coefficient (NSE), Bias Percentage (PBias), the RMSE-observations and the Standard deviation Ratio (RSR) were used to check collinearity, simulation, deviation and approximation respectively between the two rain estimation models. General results indicate that the $R^2 = 0.91$, NSE = 0.88, PBias = -0.24 and RSR = 0.35. This attests that the CHIRPS Satellite gridded datasets provide a good approximation and simulation of *in situ* station data with high collinearity and minimum deviation. This can be attributed to the spatial resolution and temporal resolution of the CHIRPS dataset as well as its gauge bias correction. The results tally with related studies [27] in other regions that have found CHIRPS datasets superior to interpolation surfaces and sparse rain gauge data in the comprehensive estimation of rainfall. With a $0.05^\circ \times 0.05^\circ$ (latitude, longitude) spatial resolution, CHIRPS satellite gridded rainfall estimates are able to provide rainfall representation at a local scale. Essentially these results reward research science in regions like Uganda that have sparse rain gauges networks characterized by incomplete, inconsistent and unreliable data with an empirically researched alternative source of rainfall data. It further provides a platform to interrogate the rainfall dynamics at a local scale in order to infuse local policy with evidence-based formulation and application.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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